

Matrix Solvers
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Lecture - 57
Preconditioned Conjugate Gradient

Welcome. So, we will be looking into Preconditioning Techniques and we have discussed about left right and split preconditioning and this session we look into how preconditioning techniques can be applied over conjugate gradient method or how conjugate gradient method can be modified if we are using a pre conditioner.

The first example of preconditioned application of the conditioner we considered; considering to be conjugate gradient method, because conjugate gradient is only applicable for symmetric positive definite matrices. And therefore, we have to see that whether we can choose proper pre conditioner so, that symmetric positive definiteness is being maintained, and then how the resultant application comes out to be.

Pre conditioners can also be used over other solve solution techniques; however, because the fact that Krylov space based solvers are faster solvers. So, we will only be discussing preconditioner over Krylov subspace based solvers, because these are already faster solvers and we need to make them more fast. For steepest descent or for Gauss Seidel we are not discussing preconditioning techniques because instead of doing that rather we will use Krylov space based solvers to get faster solvers solutions. But when Krylov space based solvers are restricted due to the poor conditioning number of the matrix we should think of using preconditioner so that we can get faster solution on top of that so, that we are not limited by the nature of the matrix; well.

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Preconditioned Conjugate Gradient

We will examine two cases:

1. Left preconditioning: $M^{-1}Ax = M^{-1}b$ with SPD M .
2. Split preconditioning: $L^{-1}AL^{-T}u = L^{-1}b$

A is SPD

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So, we will discuss two cases left preconditioning which is M inverse Ax is equal to M inverse b choosing symmetric positive definite M so, that the this matrix remains symmetric sorry sorry. So, that this matrix M inverse A this matrix remain symmetric positive definite. And conjugate gradient is only applicable when A is also a symmetric positive definite matrix.

So, if M is symmetric positive definite, M inverse A will remain symmetric positive definite and L inverse a L in L inverse AL inverse transpose will also be a systematic positive definite matrix. So, conjugate gradient will be applicable here both these equations can be solved using conjugate gradient. Now, we will see how what is the implementation of that.

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Conjugate Gradient Method - Original Algorithm

Start with guess x_0 , which gives $r_0 = Ax_0 - b$, set $p_0 = r_0$

Obtain α , update x and r

Obtain β using updated r

Update p

Iterate for convergence




$$\alpha_j = \frac{(r_j, r_j)}{(Ap_j, r_j)} \quad \beta_j = \frac{(r_{j+1}, r_{j+1})}{(r_j, r_j)}$$

$$x_{j+1} = x_j + \alpha_j p_j$$

$$r_{j+1} = r_j - \alpha_j Ap_j$$

$$p_{j+1} = r_{j+1} + \beta_j p_j$$

$r_{j+1} = r_j - \alpha_j Ap_j$ is orthogonal to r_j

So, original conjugate gradient method without any preconditioning it started. So, it starts with a guess x_0 and computes the initial residual r_0 is equal to $Ax_0 - b$ and sets p_0 is equal to r_0 and then obtain α and update x and r α is obtained using the a conjugate c of p vectors and orthogonalization of r vectors which is $r_j^T r_j - Ap_j^T r_j$ by $Ap_j^T r_j$ is α_j similarly, we obtain another parameter β_j based on which p will be updated.

So, obtained α you and update x and r . So, one α is obtained x and r is updated, and now use the updated r to obtain β and once β is obtained, update the auxiliary vector p and then iterate for converges; that means, do these steps again and again till you get a converge solution where the residual is a very small value; the mod of the L_2 norm of this vector is a very small L_2 norm of r is very small.

So, now we will see how, if we consider a preconditioned system, how these equations will be modified One idea can be that you explicitly compute an M inverse multiply that with a , get $M^{-1}a$ multiply that with b and solve it. But explicitly computing M^{-1} might be of problem at different stages because we are thinking of inverting a matrix or we are thinking of getting LU transformation of one particular matrix and then getting inversion and then doing a matrix multiplication.

So, this might be of more complication rather we will start with a matrix which is a form $M^{-1}A$, and we will assume that through some method we are getting the M^{-1}

a from how we will discuss it later. And then we apply conjugate gradient method over that M inverse a matrix. However, we will keep in mind that our original Krylov subspaces based on r_0 a r_0 s square r_0 etcetera. So, while calculating r we use the property that r_{j+1} r_j minus $\alpha_j A p_j$ is orthogonal to r .

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Left Preconditioned Conjugate Gradient

We will try to obtain steps for: $M^{-1}Ax = M^{-1}b$ with SPD $M=LL^T$

If $M=LL^T$, $M^{-1}A$ is symmetric
Therefore, CG steps can be obtained.

We start with initial guess, x_0

$z_0 = M^{-1}b - M^{-1}Ax_0$ is the residual for the new system.

The original equation has residual $r_0 = b - Ax_0$

So, $z_0 = M^{-1}r_0$

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So, left preconditioning of conjugate gradient, will try to obtain steps for M inverse Ax is equal to M inverse A with M being symmetric positive definite, LL transpose. If M is LL transpose M inverse A is also symmetric therefore, conjugate gradient can be obtained. We start with an initial guess x_0 ; z_0 is a new residual which is M inverse b minus M inverse Ax_0 because the new equation system is M inverse Ax minus M inverse b the new residual is M inverse Ax_0 subtracted from M inverse b it is the new residual.

The original residual equation has residual r_0 is equal to b minus Ax_0 . The relation between the original residual and the new residual can be obtained as z_0 is equal to M inverse r_0 . So, now the if we are thinking of solving this equation, we have to go with a new residual which is z_0 or z_0 .

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Conjugate Gradient Steps for Left Preconditioned Equation

The preconditioned matrix equation: $M^{-1}Ax = M^{-1}b$

The residual of the above equation can be updated as (z)

$$z_{j+1} = z_j + \alpha_j M^{-1}Ap_j$$

Now, the residuals of this system will be M-orthogonal. So,

$$z_j^T M z_{j+1} = 0$$

This gives the parameter α as:

$$\alpha_j = \frac{(z_j^T M z_j)}{\left((M^{-1}Ap_j)^T M z_j \right)} = \frac{(z_j, z_j)_M}{(M^{-1}Ap_j, z_j)_M}$$

Handwritten notes on the slide:
 $Ax = b$
 $r_{i+1} = r_j + \alpha_j AP_j$

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The precondition matrix equation is $M^{-1}Ax = M^{-1}b$, the residual of the above equation can be updated as very similarly $M^{-1}A$ is a coefficient matrix now. So, if we can remember our older update was $r_{j+1} = r_j + \alpha_j Ap_j$, that is our older update for $Ax = b$ equation.

Now, we have an equation $M^{-1}Ax = M^{-1}b$, and the residual is z . So, z can be updated it is a very similarly as $z_{j+1} = z_j + \alpha_j M^{-1}Ap_j$. Now, r_j and r was orthogonal as we are discussing $M^{-1}Ap_j$ when we discussing a matrix, now when we will discuss a M^{-1} a matrix the new residual z_{j+1} and z_j will be M orthogonal; that means, $z_{j+1}^T M z_j = 0$. So, dot product of z_j with $M z_{j+1}$ is equal to 0.

That gives the parameter α as $\alpha_j = z_j^T M z_j$ divided by if we substitute this here, if you substitute the z_{j+1} here we get an α_j . So, we will substitute this as z_{j+1} and we will get an equation through which we can get $\alpha_j = z_j^T M z_j$ by $(M^{-1}Ap_j)^T M z_j$. So, this is M product M dot product of z_j $z_j^T M z_j$ and this will be M dot product of $M^{-1}Ap_j$ and z_j . So, we will see how to simplify these products.

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Conjugate Gradient Steps for Left Preconditioned Equation

Further, $M^{-1}Ax = M^{-1}b$ | $Ax = b$
 $p_{j+1} = z_{j+1} + \beta_j p_j$ | $p_{j+1} = r_{j+1} + \beta_j p_j$

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Further the auxiliary vector p can be updated this auxiliary vector is now, not auxiliary vector of x is equal to b rather auxiliary vector of M inverse Ax is equal to M inverse b . So, the update will have a relation with the new residual z earlier for Ax is equal to b . So, this is for M inverse x Ax is equal to M inverse b this is for this equation. For Ax is equal to b the relation was something like $r_{j+1} = z_{j+1} + \beta_j p_j$.

So, for the M inverse Ax system this will be $p_{j+1} = z_{j+1} + \beta_j p_j$ M inverse. This is the relation for Ax is equal to b conjugate gradient therefore, this should be similarly we can find out the relation for p update of the auxiliary vector in conjugate gradient applied over M inverse Ax is equal to M inverse M or p_j is equal to $z_j + \beta_j p_{j-1}$.

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Conjugate Gradient Steps for Left Preconditioned Equation

Further, $p_{j+1} = z_{j+1} + \beta_j p_j$ or, $p_j = z_j + \beta_j p_{j-1}$



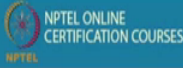

So:

$$\begin{aligned} (M^{-1} A p_j, z_j)_M &= ((M^{-1} A p_j)^T M (p_j - \beta_j p_{j-1})) \\ &= ((M^{-1} A p_j)^T M p_j) - \beta_j ((M^{-1} A p_j)^T M p_{j-1}) \\ &= ((M^{-1} A p_j)^T M p_j) = (M^{-1} A p_j, p_j)_M \end{aligned}$$

$(M^{-1} B)^T$
 $= B^T M^{-T}$
 $= B^T M^{-1}$

P is A-conjugate

As M is symmetric as $M = LL^T$

So, what we have already obtain the dot product between p_j and z_j now we will see how can we modify this. So, you got a relationship p_j is equal to z_j plus p_j minus 1.

So, this the given dot product which is $M^{-1} A p_j z_j^T M$ is equal to $M^{-1} A p_j^T M$ into z_j which will be the z the term z_j will be p_j minus $\beta_j p_{j-1}$ and this is written from here. So, when we will do this we will have $A p_j^T M^{-1} M$ inverse transpose and $M^{-1} M$ inverse transpose is same as M^{-1} because M is a symmetric matrix. So, we will have a minus and that other part will be $\beta_j M^{-1} p_{j-1}^T M p_j$.

Now, if we. So, we break it down basically $M^{-1} A p_j^T M p_j$ minus β_j which is a constant amount of it scalar and come out of it $M^{-1} A p_j^T M^{-1} p_j$. And then we can write M^{-1} say B M^{-1} B^T is equal to $B^T M^{-1}$ and as M is a symmetric matrix. So, this will be $B^T M^{-1}$.

So, this will be $A p_j^T M^{-1} M p_j$ $M^{-1} M$ will be pr identity matrix similarly this is $A p_j^T M^{-1} M p_j$ and p_j and $p_j^T p_j$ will be a 0 vector because p is an a conjugate matrix p is a conjugate. So, we will see that this term will become 0 you can work it out this is just one step and this will be $M^{-1} A p_j^T M p_j$ or $M^{-1} A p_j^T p_j$ of M as M is symmetric or $M = LL^T$.

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Conjugate Gradient Steps for Left Preconditioned Equation

$$\begin{aligned}
 \text{Also, } (M^{-1} A p_j, p_j)_M &= ((M^{-1} A p_j)^T M p_j) \\
 &= ((M p_j)^T M^{-1} A p_j) \\
 &= (p_j^T \underline{I} M^{-1} A p_j) \quad M^T = M \\
 &= (p_j^T A p_j) = (A p_j, p_j)
 \end{aligned}$$

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Further what we are discussing $(M^{-1} A p_j, p_j)_M$, M is $M^{-1} A p_j$ transpose $M p_j$ which is $(M p_j)^T M^{-1} A p_j$ because we can change the order for in the dot product $M^{-1} p_j p_j^T M$ transpose M transpose $M^{-1} A p_j$, and as M transpose M is symmetric. So, M transpose is equal to M . So, this will be an identity matrix and we will get $p_j^T A p_j$ or $A p_j$ dot p_j .

So, the denominator of the alpha calculation is simplified to $A p_j$ transpose p_j and remember this is the denominator what we obtained in conjugate gradient method also. However, the k v it is that an p_j is calculated differently in this method. Because this is p_j is an auxiliary vector of $M^{-1} A x$ is equal to $M^{-1} b$ not for $A x$ is equal to b .





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Conjugate Gradient Steps for Left Preconditioned Equation

Also, $(M^{-1}Ap_j, p_j)_M = ((M^{-1}Ap_j)^T Mp_j)$
 $= ((Mp_j)^T M^{-1}Ap_j)$
 $= (p_j^T M^T M^{-1}Ap_j)$
 $= (p_j^T Ap_j) = (Ap_j, p_j)$ M is symmetric as $M=LL^T$

Now, $z = M^{-1}b - M^{-1}Ax = M^{-1}r$ $\alpha_j =$

So: $(z_j, z_j)_M = z_j^T Mz_j = z_j^T r_j = (z_j, r_j)$

Now also z is equal to M inverse b minus M inverse Ax is equal to M inverse r . So, the M dot product of $z_j z_j$ which is z_j transpose Mz_j can be written as z_j transpose r_j or z_j dot r_j . So, my new α_j which was equal to what was the initial form of α_j we will again just once check.

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Conjugate Gradient Steps for Left Preconditioned Equation





The preconditioned matrix equation: $M^{-1}Ax = M^{-1}b$

The residual of the above equation can be updated as

$$z_{j+1} = z_j + \alpha_j M^{-1}Ap_j$$

Now, the residuals of this system will be M -orthogonal.
 So, $z_j^T Mz_{j+1} = 0$

This gives the parameter α as: $\alpha_j = \frac{(z_j^T Mz_j)}{((M^{-1}Ap_j)^T Mz_j)} = \frac{(z_j, z_j)_M}{(M^{-1}Ap_j, z_j)_M}$ $\left(\frac{z_j, z_j}{(p_j, Ap_j)} \right)$

The α_j was, $z_j z_j M$ by M inverse $Ap_j z_j$ and this is now transferred to z_j dot r_j and this is transfer to P_j dot $A p_j$. This will be the new values the final form of α , which is a conjugate gradient solver algorithm will need to compute.

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Conjugate Gradient Steps for Left Preconditioned Equation

So, the left preconditioned CG steps are:

Start with guess x_0 , which gives $z_0 = M^{-1}Ax_0 - M^{-1}b$, set $p_0 = z_0$ and $r_0 = M^{-1}z_0$

Obtain α , update x , r and then z

Obtain β using updated r

Update p

$$\alpha_j = \frac{(r_j, z_j)}{(Ap_j, r_j)} \quad \beta_j = \frac{(z_{j+1}, z_{j+1})_m}{(z_j, z_j)_m}$$

$$\begin{aligned} x_{j+1} &= x_j + \alpha_j p_j \\ r_{j+1} &= r_j - \alpha_j Ap_j \\ z_{j+1} &= M^{-1}r_{j+1} \\ p_{j+1} &= z_{j+1} + \beta_j p_j \end{aligned}$$

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So, the left precondition conjugate gradient steps will be start with x_0 , which will give z_0 is equal to guess x_0 , which will give the new residuals z_0 is equal to $M^{-1}Ax_0 - M^{-1}b$ set p_0 is equal to z_0 and r_0 is equal to $M^{-1}z_0$.

Obtain α and then update x and r and then z . So, if we can update r you can update z or the same and obtain β using the updated r . So, then the α is equal to $\frac{(r_j, z_j)}{(Ap_j, r_j)}$ and you will obtain x_{j+1} is equal to $x_j + \alpha_j p_j$. So, this also gives a direct way to update x instead of looking into z because x is the solution vector. So, x will follow exactly same relation as it was following in the conjugate gradient method of x is equal to b . It will follow the same relation in the conjugate gradient method of $M^{-1}Ax$ is equal to b because x remain same in the both in both the cases.

And r_{j+1} . So, x_{j+1} is equal to $x_j + \alpha_j p_j$ similarly r_j can be obtained as $r_j - \alpha_j Ap_j$ just substitute this into x is equal to b . x is equal to b equation is still holding and z_{j+1} is $M^{-1}r_{j+1}$. So, again it becomes important here to compute M^{-1} ; M^{-1} should be readily available with us, instead of actually looking into a LU factorization of a matrix and getting the lower transfer lower triangular form multiplying into upper triangular and inverse etcetera M^{-1} should be readily available that we need to check.

Later I will say that M how M is evaluated I will come into it later, which is also a very important part of this methods, but we will see that how them algorithms are modified provided we know to evaluate M and we are ready with M inverse or M inverse a in certain cases.

So, once z is updated you can update β is j plus 1 z j plus 1, z j plus once in dot product by z j z j M dot product. So, earlier there are β was dot product of the vectors now they are M products. And once β is updated update p as p is equal to r r j plus 1 plus β j p j p z j sorry it is not r now z , z p j plus 1 is z j plus 1 β j p j . And then you can carry this p and r and z to get the new alpha new beta and continue on the iteration loop exactly the same way what you have down in conjugate gradient method, iterate for convergence.

The conjugated ends will probably once look into the methods the conjugate gradient algorithm. Now can be formed using all these steps; starting with these steps start with these guess use all these steps and then do the iterations.

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Left preconditioned CG- Algorithm

1. Compute $r_0 := b - Ax_0$, $z_0 = M^{-1}r_0$, and $p_0 := z_0$
2. For $j = 0, 1, \dots$, until convergence Do:
3. $\alpha_j := (r_j, z_j) / (Ap_j, p_j)$
4. $x_{j+1} := x_j + \alpha_j p_j$
5. $r_{j+1} := r_j - \alpha_j Ap_j$
6. $z_{j+1} := M^{-1}r_{j+1}$
7. $\beta_j := (r_{j+1}, z_{j+1}) / (r_j, z_j)$
8. $p_{j+1} := z_{j+1} + \beta_j p_j$
9. EndDo

Symmetry of the matrix is preserved

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Which is compute r_0 is equal to b minus Ax_0 z_0 is M inverse r_0 p_0 is equal to z_0 for different iteration levels first compute α r j dot z j by Ap j dot p j . You know now in this calculation at least no M product is needed M is not needed here M was once needed at M inverse from here, but here M is not needed then x j plus 1 is equal to x j plus α j p j r j plus 1 is equal to r j minus α j Ap j z j plus 1. So, this and this if this holds

because this is the exactor remains essentially same, this should hold then by b minus x we can get this relation this one once r is obtain z is equal to M inverse r.

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Left preconditioned CG- Algorithm

1. Compute $r_0 := b - Ax_0$, $z_0 = M^{-1}r_0$, and $p_0 := z_0$
2. For $j = 0, 1, \dots$, until convergence Do:
3. $\alpha_j := (r_j, z_j) / (Ap_j, p_j)$
4. $x_{j+1} := x_j + \alpha_j p_j$
5. $r_{j+1} := r_j - \alpha_j Ap_j$
6. $z_{j+1} := M^{-1}r_{j+1}$
7. $\beta_j := (r_{j+1}, z_{j+1}) / (r_j, z_j)$
8. $p_{j+1} := z_{j+1} + \beta_j p_j$
9. EndDo

Handwritten notes on the right side of the slide:

$$r = b - Ax$$

$$z = M^{-1}b - M^{-1}Ax$$

$$= M^{-1}r$$

$$\beta = \frac{(z_{j+1}, z_{j+1})}{(z_j, z_j)} M$$

Handwritten note at the bottom left: $M^{-1}z_j$

So, we should know this that r is equal to b minus A x z is equal to M inverse b minus M inverse Ax which is the precondition system sorry M inverse r.

So, then we get z is equal to M inverse r plus 1, beta is equal to r plus 1 z j plus 1 by r j z j which is earlier we have seen that beta is equal to z j plus 1 z j plus 1 M by z j z j M. Now, z transpose z transpose M transpose z sorry. So, what is z j plus 1?

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Left preconditioned CG- Algorithm

1. Compute $r_0 := b - Ax_0$, $z_0 = M^{-1}r_0$, and $p_0 := z_0$
2. For $j = 0, 1, \dots$, until convergence Do:
3. $\alpha_j := (r_j, z_j) / (Ap_j, p_j)$
4. $x_{j+1} := x_j + \alpha_j p_j$
5. $r_{j+1} := r_j - \alpha_j Ap_j$
6. $z_{j+1} := M^{-1}r_{j+1}$
7. $\beta_j := (r_{j+1}, z_{j+1}) / (r_j, z_j)$
8. $p_{j+1} := z_{j+1} + \beta_j p_j$
9. EndDo

Handwritten notes on the left side of the slide:

$$(z_j, z_j) M$$

$$= z_j^T M z_j$$

$$= z_j^T r_j$$

$$= (z_j, r_j)$$

Handwritten notes on the right side of the slide:

$$r = b - Ax$$

$$z = M^{-1}b - M^{-1}Ax$$

$$= M^{-1}r$$

$$\beta = \frac{(z_{j+1}, z_{j+1})}{(z_j, z_j)} M$$

$$= \frac{(z_{j+1}, r_{j+1})}{(z_j, r_j)}$$

$z_j^T M z_{j+1}$ this will be $z_j^T M z_{j+1}$ (Refer Time: 20:44) some way redo it we are trying to evaluate the beta which will be equal to same in a while we can check that that $z_j^T M z_j$, this product is equal to $z_j^T M z_j$. And $M z_j$ is equal to r_j . So, $z_j^T M z_j$ or $z_j^T r_j$ $z_j^T r_j$.

So, this will be $z_j^T M z_{j+1}$ by $z_j^T M z_j$ this product will be this. So, we will get this particular beta evaluation from here. $z_j^T M z_{j+1}$ will be nothing, but dot product between $z_j^T M z_{j+1}$ and $z_j^T M z_j$ and if we write it for better clarity.

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Left preconditioned CG- Algorithm

1. Compute $r_0 := b - Ax_0$, $z_0 = M^{-1}r_0$, and $p_0 := z_0$
2. For $j = 0, 1, \dots$, until convergence Do:
3. $\alpha_j := (r_j, z_j) / (Ap_j, p_j)$
4. $x_{j+1} := x_j + \alpha_j p_j$
5. $r_{j+1} := r_j - \alpha_j Ap_j$
6. $z_{j+1} := M^{-1}r_{j+1}$
7. $\beta_j := (r_{j+1}, z_{j+1}) / (r_j, z_j)$
8. $p_{j+1} := z_{j+1} + \beta_j p_j$
9. EndDo

Symmetry of the matrix is preserved

Handwritten notes on the slide include:
 $(z_j, z_j)^M$
 $z_j^T M z_j$
 $z_j^T r_j$
 (z_j, r_j)
 (z_j, z_j)
 $r = b - Ax$
 $z = M^{-1}b - M^{-1}Ax$
 $= M^{-1}r$
 $\beta = \frac{(z_{j+1}, z_{j+1})^M}{(z_j, z_j)^M}$
 $= \frac{(z_{j+1}, r_{j+1})}{(z_j, r_j)}$

And this will be $z_j^T M z_{j+1}$ because $z_j^T M z_j$ in product is $z_j^T r_j$ and divided by $z_j^T M z_j$, which is calculated here and we will get p_{j+1} is equal to $z_{j+1} + \beta_j p_j$ the same way it should be (Refer Time: 22:58).

So, we get a; what we see that symmetricity of the matrixes preserved, that is how the M is chosen. So, that M inverse a is symmetric. And the solution is essentially very similar with the older conjugate gradient method; however, a new matrix inversion is added. This is a new matrix inversion which is added that i have to calculate M inverse and that is what we are telling that M this will be of further deliberation at the later stages that how M inverse should be obtained. So, that these steps do not add any extra overwrite here.

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Split Preconditioned Conjugate Gradient

$$L^{-1}AL^{-T}u = L^{-1}b$$

Define the following vectors and matrix:

$$\begin{aligned}\hat{p}_j &= L^T p_j \\ u_j &= L^T x_j \\ \hat{r}_j &= L^T z_j = L^{-1}r_j \\ \hat{A} &= L^{-1}AL^{-T}.\end{aligned}$$

So, the preconditioned equation system is: $\hat{A}u = L^{-1}b$

The slide also contains handwritten notes: $x = L^{-T}u$ and $u = L^T x$.

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We go to the split precondition conjugate gradient which is $L^{-1}AL^{-1}$ in $L^{-1}b$. u is equal to $L^{-1}b$, and this also needs solution of the equation that x is equal to $L^{-T}u$. And, so you get the following vectors and matrices \hat{p} is equal to $L^T p$, u is equal to $L^T x$, \hat{r} is equal to $L^T z_j = L^{-1}r_j$, and \hat{A} is equal to $L^{-1}AL^{-T}$.

So, that will give me u is equal to $L^{-T}x$, x is equal to $L^T u$, \hat{r} is equal to $L^T z_j$, which is $L^{-1}r_j$ because L^{-1} yeah this will see later this comes from the previous discussion. So, \hat{r} is equal to $L^T z_j$; z_j is the new vector and this is $L^{-1}r_j$. And \hat{A} is equal to $L^{-1}AL^{-T}$. And the preconditioned equation system is $\hat{A}u = L^{-1}b$. So, this becomes this equation system this becomes $\hat{A}u = L^{-1}b$.

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Split Preconditioned Conjugate Gradient

Now, a CG method similar to left preconditioned CG can be developed

Also, the following relations can be utilized to replace $z_j = M^{-1}r_j$ and $p_j = z_{j+1} + \beta p_j$ by the new residual and auxiliary variables in split preconditioned system

$$(r_j, z_j) = (r_j, L^{-T}L^{-1}r_j) = (L^{-1}r_j, L^{-1}r_j) = (\hat{r}_j, \hat{r}_j).$$

Similarly,

$$(Ap_j, p_j) = (AL^{-T}\hat{p}_j, L^{-T}\hat{p}_j)(L^{-1}AL^{-T}\hat{p}_j, \hat{p}_j) = (\hat{A}\hat{p}_j, \hat{p}_j).$$

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Now, conjugate gradient method similar to the left preconditioned conjugate gradient can be developed. And this method there is the following relationships can be utilized which we have already seen with an older vector z_j is equal to $M^{-1}r_j$ and p_j is equal to $z_{j+1} + \beta p_j$ by the new residual and auxiliary variables in the precondition systems. So, similarly we will get $r_j \cdot z_j$ is equal to $\hat{r}_j \cdot \hat{r}_j$ and $Ap_j \cdot p_j$ is equal to $\hat{A}\hat{p}_j \cdot \hat{p}_j$.

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Split preconditioned CG- Algorithm

1. Compute $r_0 := b - Ax_0$; $\hat{r}_0 = L^{-1}r_0$; and $p_0 := L^{-T}\hat{r}_0$.
2. For $j = 0, 1, \dots$, until convergence Do:
3. $\alpha_j := (\hat{r}_j, \hat{r}_j) / (Ap_j, p_j)$
4. $x_{j+1} := x_j + \alpha_j p_j$
5. $\hat{r}_{j+1} := \hat{r}_j - \alpha_j L^{-1}Ap_j$
6. $\beta_j := (\hat{r}_{j+1}, \hat{r}_{j+1}) / (\hat{r}_j, \hat{r}_j)$
7. $p_{j+1} := L^{-T}\hat{r}_{j+1} + \beta_j p_j$
8. EndDo

The left preconditioned CG is supposed to solve $\hat{A}u = L^{-1}b$ and then find $L^T x = u$

In the present algorithm, the scheme has been already modified for solving $Ax = b$ without evaluating u

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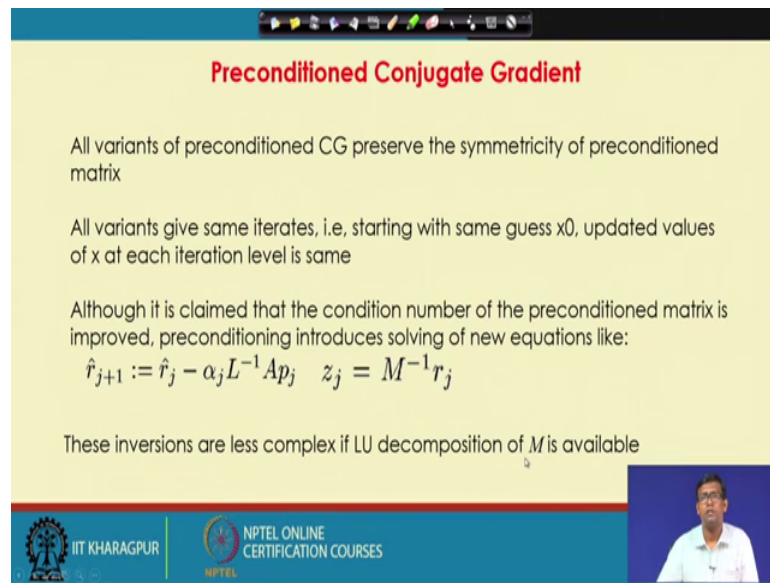
So, the method this is the derivation of the method is very similar to the left precondition method. Only thing we have a new equation $L^{-T}u = b$, and $u = L^T x$ then equation system. So, we compute the initial residual $r = b - Ax$ get $L^{-T}r$ r is r $\hat{=}$ $L^{-T}r$ obtain p $\hat{=}$ $L^{-T}r$.

And instead of directly write p $\hat{=}$ z this is the new form of p , then we obtained α we obtained update x update r based on x update. So, you can write $b - Ax = 0$ and get r from x and then update β and get the p and do the iterations.

Then lift left precondition CG supposed to solve $\tilde{A}u = L^{-1}b$ and then for find $L^T x = u$; however, in the present algorithm we are not explicitly evaluating u rather it is modified to solve $Ax = b$. So, it is taken care of that both these sets of equations are solved together, by the way we are defining \tilde{r} and p and then using this p to evaluate update x both this equation systems are taken care of.

So, we are not solving it separately; however, something like L^{-T} solution is required when we are finding out p and $L^{-1}A$ this product is required when we are finding out \tilde{r} . So, we are saying that any of the condition precondition system is adding some sort of overwrite in terms of solving a new equation system. So, this equation system the L^{-T} or $L^{-1}A$ this equation systems should be very; we will have should have much less complexity to solve you should have some way readily available solution in n steps, we should not encounter in cube number of steps some method we in which we can get n steps.

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Preconditioned Conjugate Gradient

All variants of preconditioned CG preserve the symmetricity of preconditioned matrix

All variants give same iterates, i.e, starting with same guess x_0 , updated values of x at each iteration level is same

Although it is claimed that the condition number of the preconditioned matrix is improved, preconditioning introduces solving of new equations like:

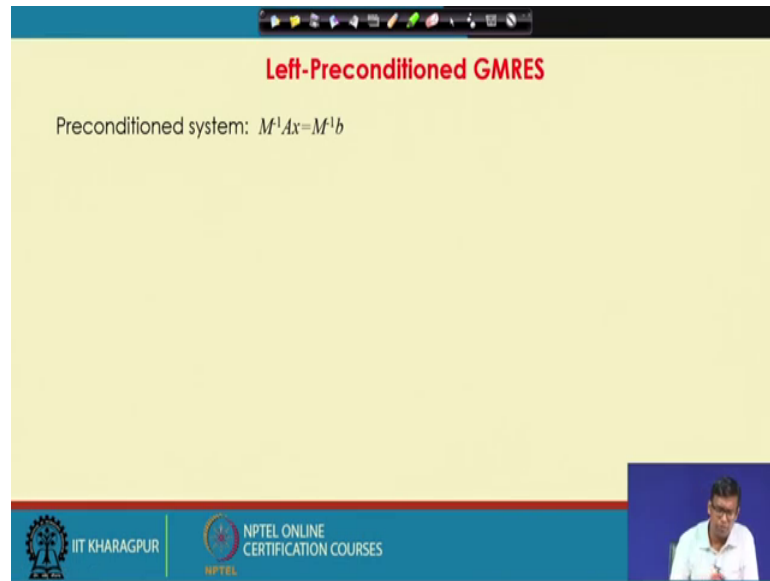
$$\hat{r}_{j+1} := \hat{r}_j - \alpha_j L^{-1} A p_j \quad z_j = M^{-1} r_j$$

These inversions are less complex if LU decomposition of M is available

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All variants of precondition CG preserve the symmetry of the precondition matrix all variants gave same iterates. So, we look in to split preconditioning we look in left preconditioning even if we think of right preconditioning, the iterate should be same that is starting with the values x_0 the updated value of x at each iteration level must be same. Although it is claimed that condition number of the precondition matrix in improve, the preconditioning increases new method introduces new equations like \tilde{r} is equal to $r - \theta L^{-1} A p_j$ or z is equal to $M^{-1} r_j$. So, the inverses are less complex; this inverse is less complex if LU decomposition is of M is already available, then the finding this inverse will be straightforward.

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Left-Preconditioned GMRES

Preconditioned system: $M^{-1}Ax = M^{-1}b$

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So, next session so, we have to see that how LU inverse of M is available, but before doing that in the next session we will look into how preconditioning of GMRES is obtained.

One group is for symmetric matrices we have looked into conjugate gradient method now for general matrices non symmetric matrices we will look into the GMRES method and how preconditioned algorithm for GMRES is available. And then we will see which is extremely important that how the inverse of the M matrix or how the actual precondition matrix and its application over the solution vectors can be are obtained so, that the computational complexities due to the preconditioning itself is not high, that add adds extra overwrite on the solution this methodology. So, we will also look into that in the next class.

Thank you.